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TRACK-BEFORE-DECLARE METHODS IN IR IMAGE SEQUENCES

Steven M. Bolen

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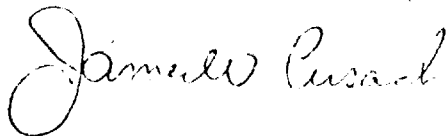


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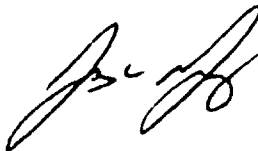
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APPROVED:



JAMES W. CUSACK, Chief
Photonics & Optics Division

FOR THE COMMANDER:



JAMES W. YOUNGBERG, LtCol, USAF
Deputy Director
Surveillance & Photonics Directorate

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13. ABSTRACT (Maximum 200 words) The development of low observable (LO) targets, such as cruise missiles and cruise-missile-carrying aircraft, can severely stress the detection and tracking capabilities of infrared (IR) surveillance systems. Long-range surveillance requires the detection and tracking of targets that are spatially unresolved and often maneuvering in a low signal-to-clutter ratio (SCR) environment. These characteristics make the LO target difficult to detect in single-frame processing techniques. However, by combining intensity information from each pixel over many frames of data it is possible to improve target detection capability. A class of long-term integration techniques for weak target detection, known as track-before-declare (TBD), will be discussed in this paper.					
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1.0 Introduction

In conventional processing systems, such as that shown in Fig. 1a, intensity data recorded by an IR sensor is fed into a signal processor. This processor outputs a high value (one) or a low value (zero) for each pixel based upon some preset decision logic. Generally, a high-valued output occurs at a pixel location when the intensity level at that pixel exceeds a predetermined threshold. As each frame of data is received from the sensor, threshold crossings are determined. This information is then passed to a track processor where data association is performed and target state estimates (i.e., tracks) are computed. Threshold crossings (or observations) determined by the signal processor can be the result of thermal emissions from true targets such as cruise missiles, cruise missile carrying aircraft or from clouds, earth radiance, solar illumination, or other sources. Observations that cannot be associated with emissions emanating from actual targets are called false alarms.

One commonly used scheme to determine observations from sensor intensity data is to form a ratio of conditional probabilities and compare it to a threshold

$$l(r) = \frac{P(r/h_0)}{P(r/h_1)} \underset{h_0}{\overset{h_1}{>}} b \quad (1)$$

where the quantity on the left is called the likelihood ratio denoted by $l(r)$ ¹, r is an intensity value located in the sample space (or frame of data), b is the threshold, and h_1 and h_0 are hypotheses that correspond to the presence and absence of a target, respectively. The likelihood ratio of (1) is simply the ratio of the conditional probability of an

¹ In this and subsequent sections, lower case type will be used to indicate scalars and lower case bold to indicate vectors.

intensity being recorded by a pixel given the presence of an actual target to the intensity being recorded given the absence of a target. These conditional probabilities are defined as the probability of detection (P_d) and probability of false alarm (P_f). The threshold, b , in (1) can be computed from the a priori probabilities and costs associated with the decision logic. Typically, the costs are set so as to maximize P_d (or minimize P_f) [1].

Targets in a high clutter environment are difficult to detect using single frame processing methods such as that described above. Low threshold settings increase the likelihood of detection (i.e., of obtaining observations resulting from true targets), but also have the adverse affect of generating a large number of false observations as well. Several temporal processing techniques have been described for improving the signal-to-clutter ratio (SCR). These techniques range in complexity from simple frame differencing to more elaborate methods for background suppression. Many of these methods are based on radar processing techniques. The frame differencing method, for example, is similar to the Moving Target Indicator (MTI) approach used in radar in which delayed doppler returns are subtracted from undelayed returns for moving target detection [2].

Processing of only a few frames of data, however, even with optimal filtering, can be inadequate for detecting dim maneuvering targets [3]. A long term integration approach is required to achieve SCRs such that thresholds can be set that maximize the probability of detection without generating a large the number of false alarms. Multi-dimensional processing methods of this type, known as track-before-declare (TBD), and sometimes by the misleading term track-before-detect, have been employed in systems as diverse as doppler radar [4] and infrared surveillance systems [5].

Unlike conventional processing schemes the TBD method

starts with a target trajectory model (track) and tries to find a set of measurements that fit the trajectory. This method creates a three dimensional search space in azimuth, elevation, and time. If such a set can be found in the sample space the presence of a target can be declared; hence, the term "track-before-declare". A ratio of a posteriori probabilities of the form

$$\ln t(h) = \frac{P(h_k/z_k)}{P(h_0/z_k)} \begin{matrix} h_k \\ > \\ h_0 \end{matrix} \quad b_t \quad (2)$$

can be computed to decide whether or not a set of measurements can be declared a target track. Here, h_k is the target track hypothesis in terms of a specified sequence of target states, h_0 is the null (no track) hypothesis, and z_k is the set of measurements over which the likelihood test is performed. When the ratio of (2) exceeds the threshold, b_t , hypothesis h_k is chosen and a target is declared.

A block diagram of the TBD processing approach is shown in Fig. 1b. Sensor intensity data is fed into a preprocessor for data preselection and/or clutter suppression. Most TBD algorithms are computationally intensive due to the large search volumes over which target tracks are identified. In practice, this large sample volume needs to be restricted to achieve real-time processing. Information from the preprocessor is sent to the TBD processor for target track detection. The TBD processor associates measurements that lie along hypothesized target tracks. This can be performed either sequentially or in a batch processing mode. In sequential methods, a score is assigned to each measurement as it is received. When the score exceeds a threshold a target detection is declared. In batch processing, a sequence of IR images is stored and each set of measurements in the data is scored. Measurement sets that exceed a threshold indicate the presence of a

target track and a target detection is declared.

As early as 1964, Sittler [6] had described an approach to perform data association for track processing and to determine the quality of the computed tracks. The data was sampled at random intervals and consisted of target signal and background noise. As each observation was determined it was given a score according to a probabilistic model of the surveillance system, possible target motions, and its correlation to previous observations. If the score exceeded a certain level the observation was used to initiate a track. Other levels could be defined to decide whether the track should be maintained or terminated. In 1975, Stein and Blackman [7] extended the work of Sittler and others. They developed a batch processing algorithm that sampled the surveillance data at discrete time intervals and made use of state space models to describe target maneuvers. In 1985, Corbeil [8] implemented a TBD algorithm for ground-based radar. His approach utilized association windows and M-out-of-N coincidence logic to detect targets with a low radar cross section (RCS). More recently, Arnold [9] has applied a dynamic programming approach to weak target detection for a staring IR sensor. This paper will discuss several methods used in TBD processing.

2.0 Surveillance Model

Derivation and discussion of the TBD processing algorithms presented in this paper will focus on applications to long range IR surveillance. The sensor system can be either scanning or staring and be located on a variety of platforms (ground-based, airborne, or space-based). Each type of system and platform has unique operating characteristics that can impact algorithm implementation. The specific constraints of each will not be addressed in this paper, however. Rather, the TBD method will be presented as a solution to the more general problem of detecting dim moving targets. In discussion of the

various approaches the following assumptions will be made:

- 1) The surveillance area is sampled at discrete time intervals.
- 2) Targets are unresolved point sources.
- 3) Target maneuvers can be modeled as finite state processes.
- 4) Many targets of varying intensities and velocities can exist within the search area at any time. These targets can enter and exit the search area randomly and trajectories of several targets can cross.
- 5) When a target exists in the surveillance area sensor intensity measurements contain target and clutter intensity components of the form

$$z(u,k) = s(u,k) + v(u,k) \quad (3)$$

where $u = (i,j)$ indicates the intensity measurement located at the ij^{th} pixel and k is the discrete time index of the measurement. Otherwise, measurements contain only background clutter intensity.

- 6) Targets are dim compared to the background clutter ($SCR < 1$) and cannot be easily detected in single frame processing methods.

3.0 Approaches

3.1 Exhaustive Search

One approach for finding target tracks in a set of IR image sequences is to perform an exhaustive search through all possible target paths in the search volume. A score is assigned to each path according to how likely it is that the

path corresponds to a track. The scoring function might include the use of intensity measurements along the path, recognizing consistencies in the observation set, and path smoothness. If the elements of the score can be correctly characterized (such as the target maneuver model, noise characteristics, etc.) then the exhaustive search is optimal. That is, the best solution can be found from the specified criterion.

The number of paths that need to be searched can be computed from

$$n_p = (n_r)^{n_t} \quad (4)$$

where n_p is the number of paths to be searched, n_r is the number of resolution cells (or pixels) of the sensor system, and n_t is the number of time intervals (or frames) over which the search is performed. It can be seen from (3) that the number of paths to be checked increases exponentially with the number of time intervals. As the number of intervals (or integration time) increases it is obvious that the number of paths to be searched can become enormous. For example, a search through just five frames of data from a staring sensor with a 64 x 128 pixel array would require checking over 10^{19} paths.

3.2 Dynamic Programming

An alternative to the exhaustive search is a method known as dynamic programming (DP). The DP approach is a sequential technique that tries to maintain the optimality of the exhaustive search, but without searching through every possible path. At each time interval it selects only those path segments that have the highest probability of being associated with a target transition. Path segments that form consistent links over the search interval would be declared as target tracks.

As an illustration, consider the example in Fig. 2 with

target transition costs as shown. Suppose that it is desired to find the lowest cost path from the first to the third interval. An exhaustive search would require checking eight paths: $a_1a_2a_3$, $a_1a_2b_3$, $a_1b_2a_3$, $a_1b_2b_3$, $b_1b_2b_3$, $b_1b_2a_3$, $b_1a_2b_3$, and $b_1a_2a_3$. The cost of each path would be calculated and the path with the lowest score would be selected. In this case, path $a_1a_2b_3$ would be chosen. In the DP approach, the lowest cost path segment is determined at each interval for each pixel. In the first interval, segments a_1a_2 and b_1b_2 would be selected and at the second interval segments a_2b_3 and b_2b_3 would be selected. Costs would then be calculated only for paths $a_1a_2b_3$ and $b_1b_2b_3$ - all other possible path hypotheses being rejected at each interval. The correct path, $a_1a_2b_3$, would again be chosen. Note that, at least in this example, the number of paths over which costs need to be computed is reduced by a factor of four over the exhaustive search approach.

3.21 DP Algorithm Implementation

In general, the DP approach is based on a maximum a posteriori (MAP) technique for estimating the state sequence of a finite state process. The process (or target) state can be defined at each time interval in terms of the target position, velocity, acceleration, etc. The state sequence is the set of target states from the first through the k th interval. The most probable target hypothesis, h_{opt} , is selected according to

$$h_{opt} = \max \left\{ \frac{P(h_k/z_k)}{P(h_0/z_k)} \right\} \quad (5)$$

where the h_k hypothesis is the set of target states

$$h_k = (\theta_1, \theta_2, \dots, \theta_k) \quad (6)$$

through the k th interval.

Derivation of a recursive algorithm for computer implementation can be determined by applying Baye's Rule to the numerator and denominator of (5)

$$\max\left(\frac{P(h_k/z_k)}{P(h_0/z_k)}\right) = \max\left(\frac{P(z_k/\theta_k)}{P(z_k/h_0)} \frac{P(h_k)}{P(h_0)}\right) \quad (7)$$

where

$$\begin{aligned} P(h_k) &= P(\theta_k, \theta_{k-1}, \dots, \theta_1) \\ &= P(\theta_k/\theta_{k-1}, \dots, \theta_1) P(\theta_{k-1}, \dots, \theta_1). \end{aligned} \quad (8)$$

If the target state transitions are assumed to form a Markov process then

$$P(h_k) = P(\theta_k/\theta_{k-1}) P(\theta_{k-1}, \dots, \theta_1) \quad (9)$$

and (7) becomes

$$\begin{aligned} \max\left(\frac{P(h_k/z_k)}{P(h_0/z_k)}\right) &= \max\left(\frac{P(z_k/\theta_k)}{P(z_k/h_0)} \frac{P(\theta_k/\theta_{k-1}) P(h_{k-1}/z_{k-1})}{P(h_0/z_{k-1})}\right). \end{aligned} \quad (10)$$

For computational convenience the log is taken of both sides and the DP scoring function is given by

$$\begin{aligned} \max(S_n) &= \log\left(\frac{P(z_k/\theta_k)}{P(z_k/h_0)}\right) \\ &+ \max_{k-1}(P(\theta_k/\theta_{k-1}) + \max(S_{k-1})) \end{aligned} \quad (11)$$

The total cumulative score, S_n , at the k^{th} interval for each measurement set consists of the log likelihood ratio of intensities from new measurements at the k^{th} interval, the

target state transition cost from the $(k-1)^{st}$ interval to the k^{th} , and the cumulative score up through the $(k-1)^{st}$ interval. The optimal path is the set of measurements associated with the maximum score at the k^{th} interval. Note that only the optimal target transition links are propagated.

An example of the DP scoring function is shown in Fig. 3. Initially, the cumulative score is simply the value of the log likelihood ratio of the intensities at each pixel. At the second interval, the likelihood ratio at each pixel is calculated, optimal transition links from the first interval to the second are found, and the new cumulative score is computed. This process is repeated at each succeeding interval. At the k^{th} interval, target detections are declared at pixels that have scores which exceed a predetermined threshold.

IR sensor intensity measurements and the output of a DP algorithm at four different time intervals are shown in Fig. 4a and 4b². The raw IR sensor scenes are grey-scale representations of the recorded thermal intensities. Hot objects are bright and cold objects are dark. The DP output scenes are grey-scale representations of the cumulative score at each pixel for a given track hypothesis. High score areas are bright and low score areas are dark. In the scenes, a target is moving slowly from right to left starting at the right of the camera's field-of-view. As can be seen in the raw sensor data the target is difficult to detect in any single frame. However, by combining information over many frames the DP algorithm is able to detect the target which is located near the center of the bright spot in the last three frames.

3.3 Matched Filter

² The DP algorithm was developed for RADC/OCSA under contract by SRI International, see [9]. The data was collected from the OCSA/Infrared Surveillance Lab at GAFB.

The matched filter method is a batch processing technique that integrates the target signal in order to maximize the SCR in the presence of additive uncorrelated clutter. For target track detection, the maximum SCR can be obtained by choosing an optimum filter based on target maneuver characteristics. In the case of one dimensional filtering the optimum filter is derived from a single domain (such as time). The application of matched filter theory to moving target detection (three dimensional filtering) can be directly extended from the one dimensional case. The three dimensional filter is based on target position (spatial location) and velocity (spatial progression through time). Selection of an optimal three dimensional filter is similar to the one dimensional case. The steps are summarized below and follow that found in [10].

3.31 One Dimensional Derivation

Consider the discrete time linear system shown in Fig. 5. The output is

$$y(k) = \sum_{p=0}^k z(p)h(k-p) \quad (12)$$

where $z(k)$ is the input and $h(k)$ is the impulse response of the system. If $z(k)$ consists of target signal and an additive clutter component the system output becomes

$$\begin{aligned} y(k) &= \sum_{p=0}^k [s(p)h(k-p) + w(p)h(k-p)] \\ &= y_o(k) + w_o(k) \end{aligned} \quad (13)$$

and the output SCR can be defined as

$$SCR_o = \frac{|y_o(k)|^2}{E(w_o^2(k))} \quad (14)$$

Let $S(m)$ and $H(m)$ denote the Discrete Fourier Transform (DFT) of the target signal and filter impulse response, respectively. The inverse DFT of the output signal, $y_o(k)$, can be written as

$$y_o(k) = 1/K \sum_{m=0}^{K-1} S(m) H(m) e^{jmk2\pi/K} \quad (15)$$

where K is the number of samples over which the transform is taken. If $w_o(k)$ is assumed white with constant power spectral density then

$$W(m) = n_o |H(m)|^2 \quad (16)$$

and the average clutter power at the output is

$$E\{w_o^2(k)\} = n_o \sum_{m=0}^{K-1} |H(m)|^2. \quad (17)$$

Substituting (15) and (16) into (14), the SCR_o becomes

$$SCR_o = \frac{1/K \left| \sum_{m=0}^{K-1} S(m) H(m) e^{jmk2\pi/K} \right|^2}{n_o/K \sum_{m=0}^{K-1} |H(m)|^2} \quad (18)$$

From Schwarz's inequality the numerator in (18) can be written as

$$1/K \left| \sum_{m=0}^{K-1} S(m) H(m) e^{jmk2\pi/K} \right|^2 > 1/K \sum_{m=0}^{K-1} |S(m)|^2 \sum_{m=0}^{K-1} |H(m)|^2. \quad (19)$$

If $H(m)$ is chosen to be $S^*(m) e^{-jmk2\pi/K}$ (* denotes complex

conjugate) then the equality in (19) holds and the maximum SCR becomes

$$SCR_{0,max} = 1/n_0 \sum_{m=0}^{K-1} |S(m)|^2. \quad (20)$$

The optimum filter is then

$$H_{opt}(m) = S(m) * e^{-jmk2\pi/K}. \quad (21)$$

Taking the inverse DFT yields

$$h_{opt}(k) = s(p-k). \quad (22)$$

This means that the output SCR can be maximized if the impulse response of the filter is set (or matched) to a time-reversed delayed version of the target signal.

3.32 Moving Target Implementation

The above results can be extended to the moving target case, as shown by Reed [11]. If the target starts at some initial position u' and moves at a velocity v the measurements are of the form

$$z(u-u'-vk) = s(u-u'-vk) + \text{noise} \quad (23)$$

The DFT of the target signal component is

$$\begin{aligned} \text{DFT}(s(u-u'-vk, k)) &= \sum_{u=0}^{U-1} \sum_{k=0}^{K-1} s(u-u'-vk, k) e^{-jmk2\pi/K} e^{-jnu2\pi/U} \\ &= S(n, m) e^{-jn2\pi(u' + vk)} \end{aligned} \quad (24)$$

and the optimum filter is chosen (in frequency domain) as

$$H_{opt}(m) = S^*(n,m)e^{jn2(u' + vk)}e^{-jmk2/K}e^{-jnu2/U}. \quad (25)$$

The block diagram for 3-D matched filtering is shown in Fig.6. The DFT is taken of the input signal over K frames and filtering is performed in the frequency domain. The output of the system produces "matched filter peaks" which are then thresholded. Peaks that exceed the threshold are declared as targets.

3.4 Multiple Hypothesis Testing

Multiple hypothesis testing (MHT) is a sequential technique that recognizes target characteristics in a sequence of intensity threshold crossings. Data association hypotheses are generated based on possible alternatives for the observations. Hypotheses are formulated, and their likelihoods computed, based on whether or not an observation was the result of a false alarm, a new target, or an existing target. If n targets exist the total number of hypotheses that can be generated by an observation is $n + 2$. Threshold detection statistics such as probability of detection (P_d), expected false alarm and target densities (denoted b_{ft} and b_{nt}), and the accuracy of target state estimates are used to derive the hypotheses probabilities. For each possible association hypothesis, H , the probability, $P(H)$, at the current interval can be computed from past hypotheses probabilities, $P(H')$, and are given by

$$P(H) = \frac{b_{ft}(1-P_d)^2}{C} P(H') \quad (26)$$

for the hypothesis that the observation was not generated by a target (where C is the total cumulative probability from the previous interval),

$$P(H) = \frac{(1-P_d)^{n-1} P_d \delta_{ij}}{C} P(H') \quad (27)$$

for the hypothesis that the j^{th} observation is associated with the i^{th} track (where g_{ij} is the likelihood function for the association), and

$$P(H) = \frac{b n t (1 - P_d)^n}{C} P(H') \quad (28)$$

for the hypothesis that the observation is a new target. These probabilities can be used in a scoring function and serve as updates to determine the mostly likely association at the current interval.

Since data association hypotheses can grow rapidly, it may become necessary to reduce the number of associations. One hypothesis reduction technique that combines hypotheses with similar characteristics is described in [12]. Standard Kalman filtering techniques can also be used to update track state estimates and compute covariances to create data association windows, as shown in Fig. 7. Observations that fall outside the window would not generate new hypotheses. The multiple hypothesis filter for data association and hypotheses generation are described in more detail in [13 and 14].

3.5 Other Methods

Other methods include morphological filtering, Hough transform techniques, and artificial neural network (ANN) applications. Morphological filtering is largely an ad hoc method that uses arithmetic logic to recognize patterns in noisy data sets [15]. In two dimensional spatial filtering applications, a geometrical figure called the filter kernel is chosen based on a priori knowledge of the target shape. A series of unions and intersections of the figure with the image set is performed and the result is a reconstruction of the target image. An example of this is shown in Fig. 8. Several IR images can be stored and three dimensional filtering of sensor intensity data over time can be

accomplished. A three dimensional kernel can be selected based on hypothesized target track patterns. The filtered outputs could be thresholded to determine target declarations.

The Hough transform has been used as a technique in computer image processing to find straight lines, circles, and parabolas in noisy two dimensional [16 and 17] data sets. The procedure is to select an appropriate coordinate transformation to map sensor data from measurement space to parameter space and then perform detection. For example, to detect straight lines in (x,y) image space the transform

$$p = x \cos(\theta) + y \sin(\theta) \quad (29)$$

can be chosen. Image space coordinates (x,y) are mapped into the parameter space coordinates (p,θ) , where p is the perpendicular distance from the origin to the line in the (x,y) coordinate system and θ is the angle of inclination of the perpendicular from the positive x -axis. Note that each point in image space corresponds to a sinusoidal 'Hough curve' in parameter space as shown in Fig. 9. Likewise, each point (p,θ) in parameter space corresponds to a line in image space. As each point a, b, c , etc. is found on line A in image space a corresponding curve is constructed in parameter space that intersects the point (p,θ') . When the number of curves that intersect this point exceed a threshold the presence of line A can be declared. Appropriate transformations could also be selected for detecting curved lines. Three dimensional sequential processing of data in (x,y,t) space can be used to find target tracks through a set of IR images.

Neural networks are processing architectures that attempt to model the functions of the brain. Applications include pattern recognition, pattern completion, and adaptive control. A neural network may consist of several layers of interconnected processing nodes. Each node

receives a set of weighted inputs from the sensor or from previous layers as shown in Fig. 10. The inputs are summed and a nonlinear function, such as the sigmoid function shown in Fig. 11, is applied to produce an output [18]. Node processing functions and the network structure itself are determined based on the intended application. Several networks have been developed for spatial pattern recognition [19]. Temporal processing architectures suitable for target track detection, known as time delayed neural networks (TDNN), have been studied for speech recognition [20]. Time delayed portions of the input signal are used as inputs to a neural network as shown in Fig. 12. Pixel intensity data can be stored from frame to frame and track detection can be performed in a batch processing mode.

4.0 Summary

Several approaches to track-before-declare applicable to long range IR surveillance have been discussed. The TBD method detects weak targets by recognizing track-like consistencies in the surveillance data. In IR signal processing the search volume is over a sequence of sensor intensity data frames. The exhaustive search approach considers all possible data sets in the search area to identify target tracks. This approach is optimal in the sense that every data set in the sample volume is considered. Data sets that conform to target track-like characteristics, including nonlinear type trajectories, are declared as target tracks. This method, however, can be very computationally intensive. A dynamic programming approach to the target track search can be implemented that preserves the optimality of the exhaustive search, but with far fewer computations. Moving target detection can also be extended to the matched filtering technique which can be shown to provide maximum SCR gain for constant velocity targets. When target trajectories are ambiguous, or are not well known, intensity thresholds can be set for each data

frame and associations can be formed to determine the origins of threshold crossings. This method generates multiple hypotheses for each observation and computes the likelihood for each association. Other approaches such as morphological filtering, Hough transform techniques, artificial neural networks, etc. can also be implemented to detect target tracks. In general, the approach is selected based on target maneuver characteristics, how well the characteristics are known, and processing resources.

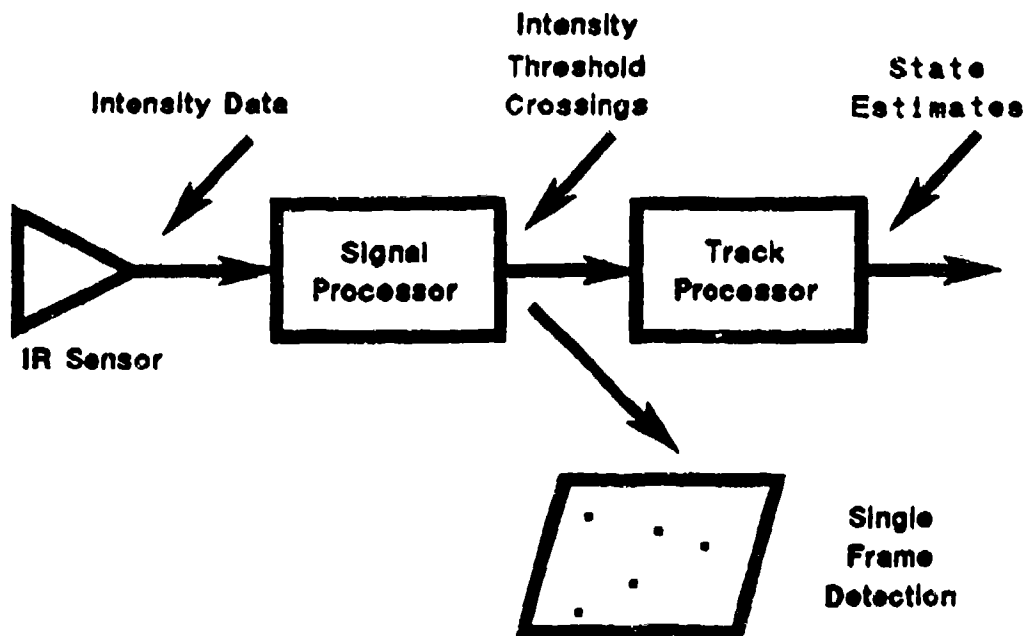


Figure 1a
Conventional Processing System

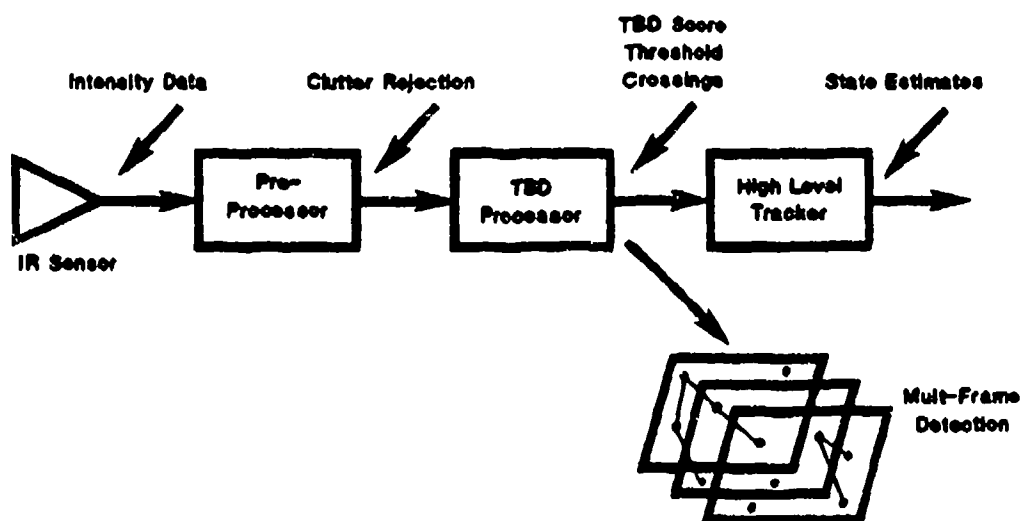
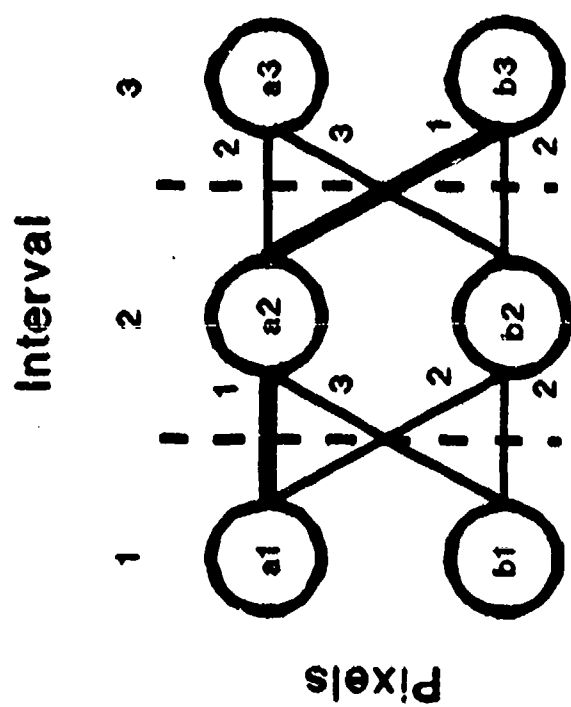


Figure 1b
TBD Processing Approach



Optimal Path = $a_1 a_2 b_3 = 2$

Figure 2
Optimal Path Selection

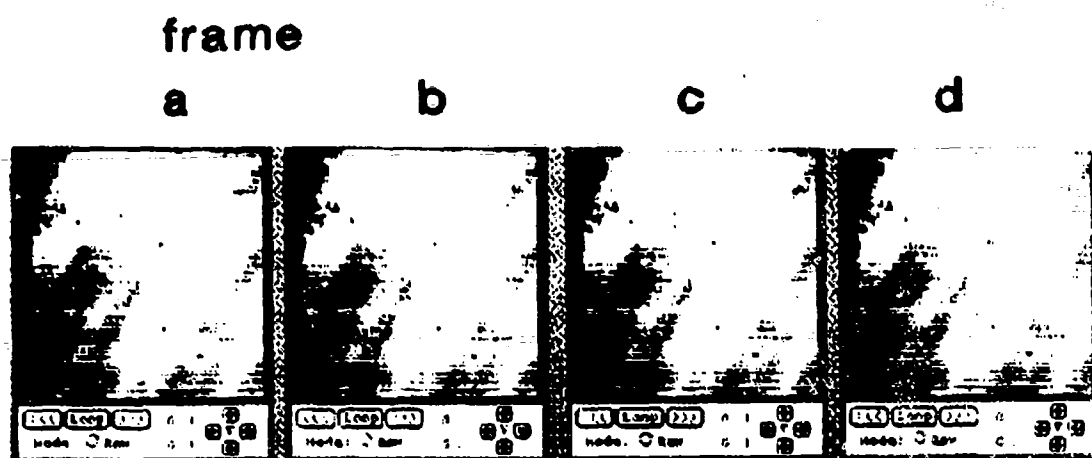


Figure 4a
Raw Sensor Intensity Data

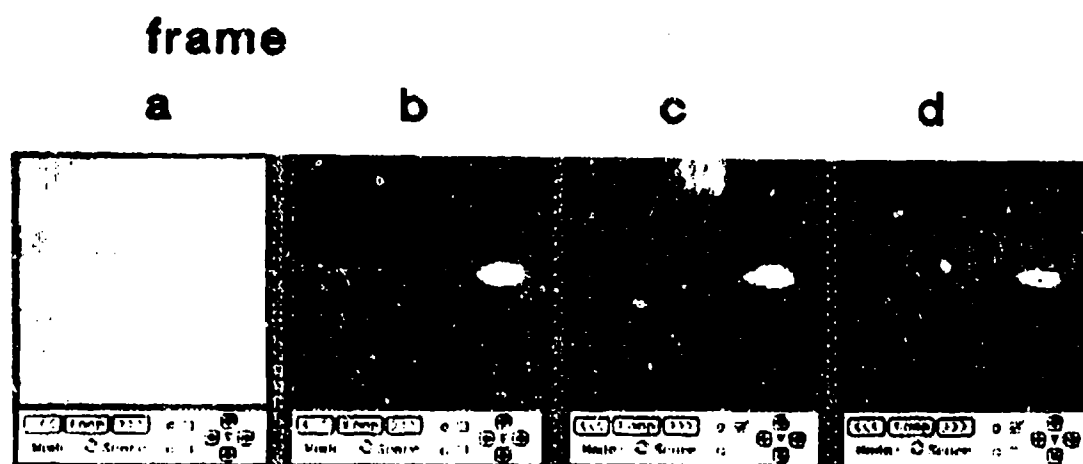


Figure 4b
DP Algorithm Output

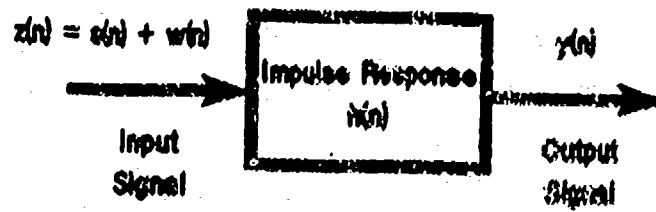


Figure 5
Linear Filter

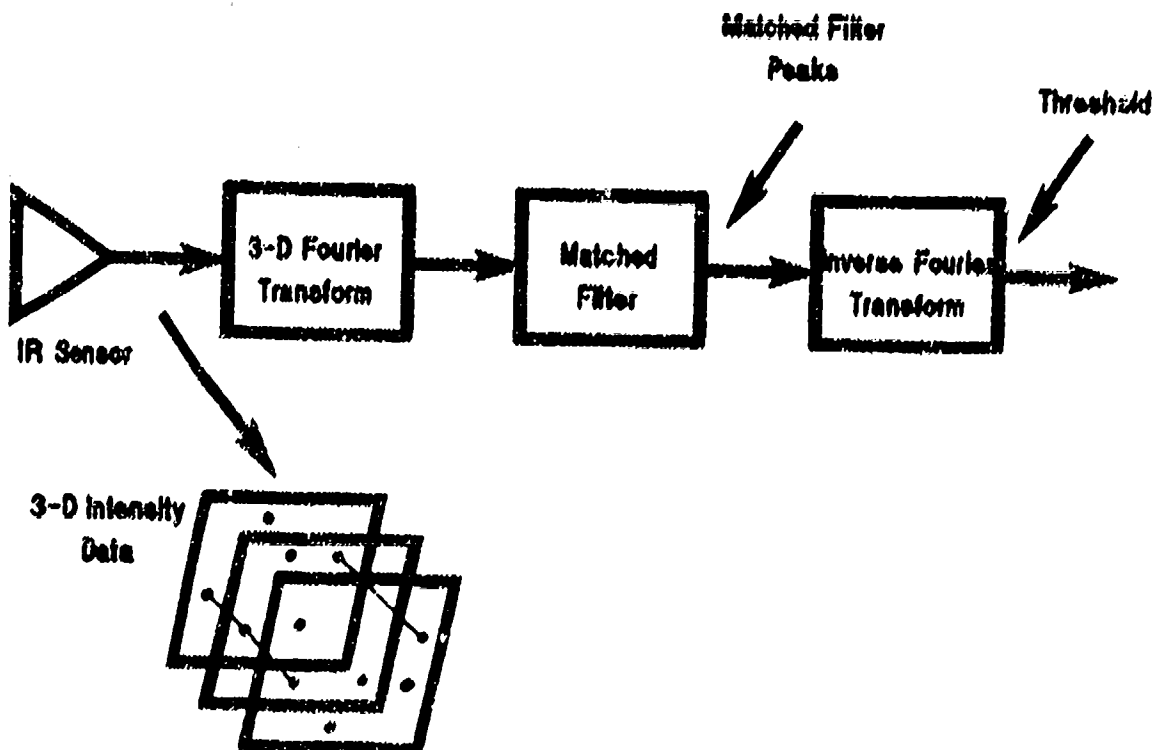


Figure 6
3-D Matched Filter Processing

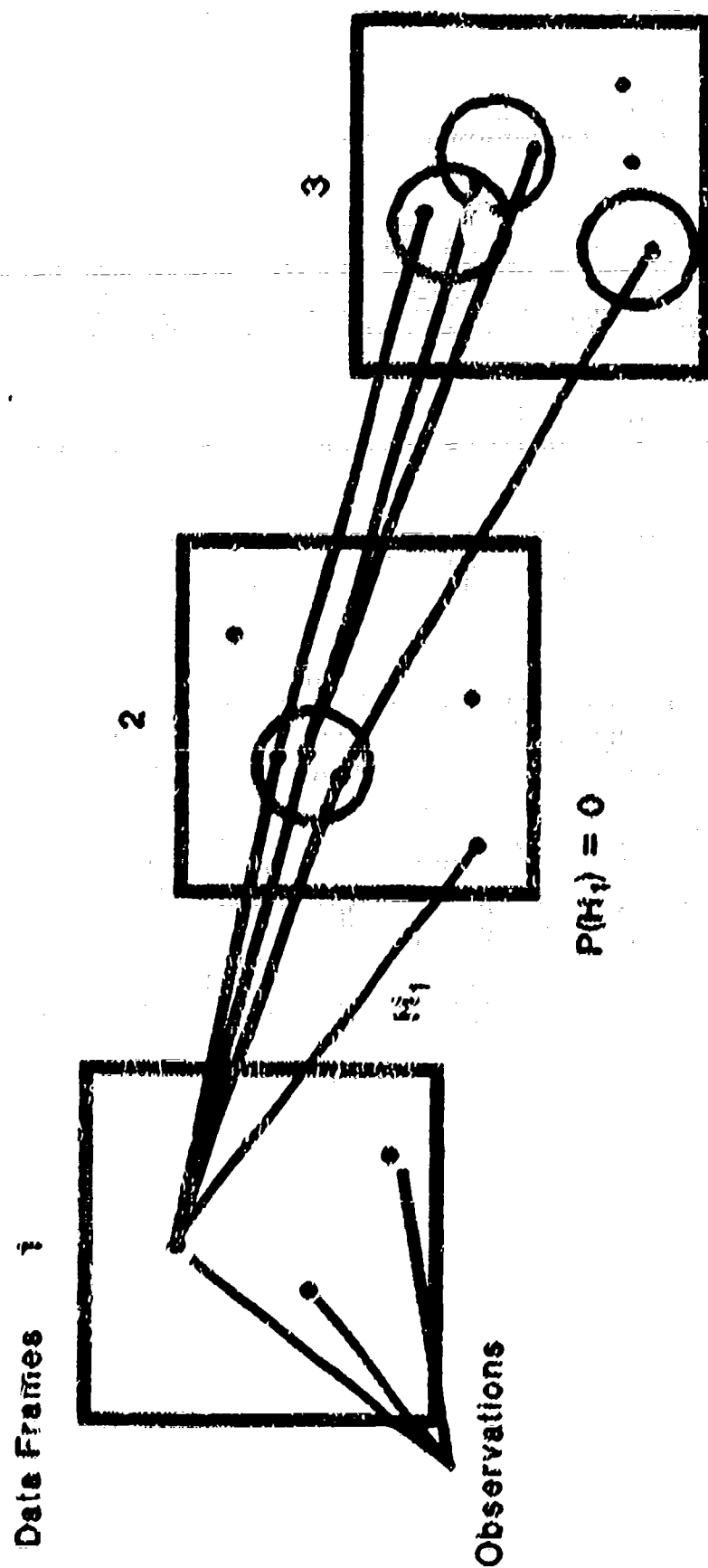


Figure 7
Hypothesis Reduction

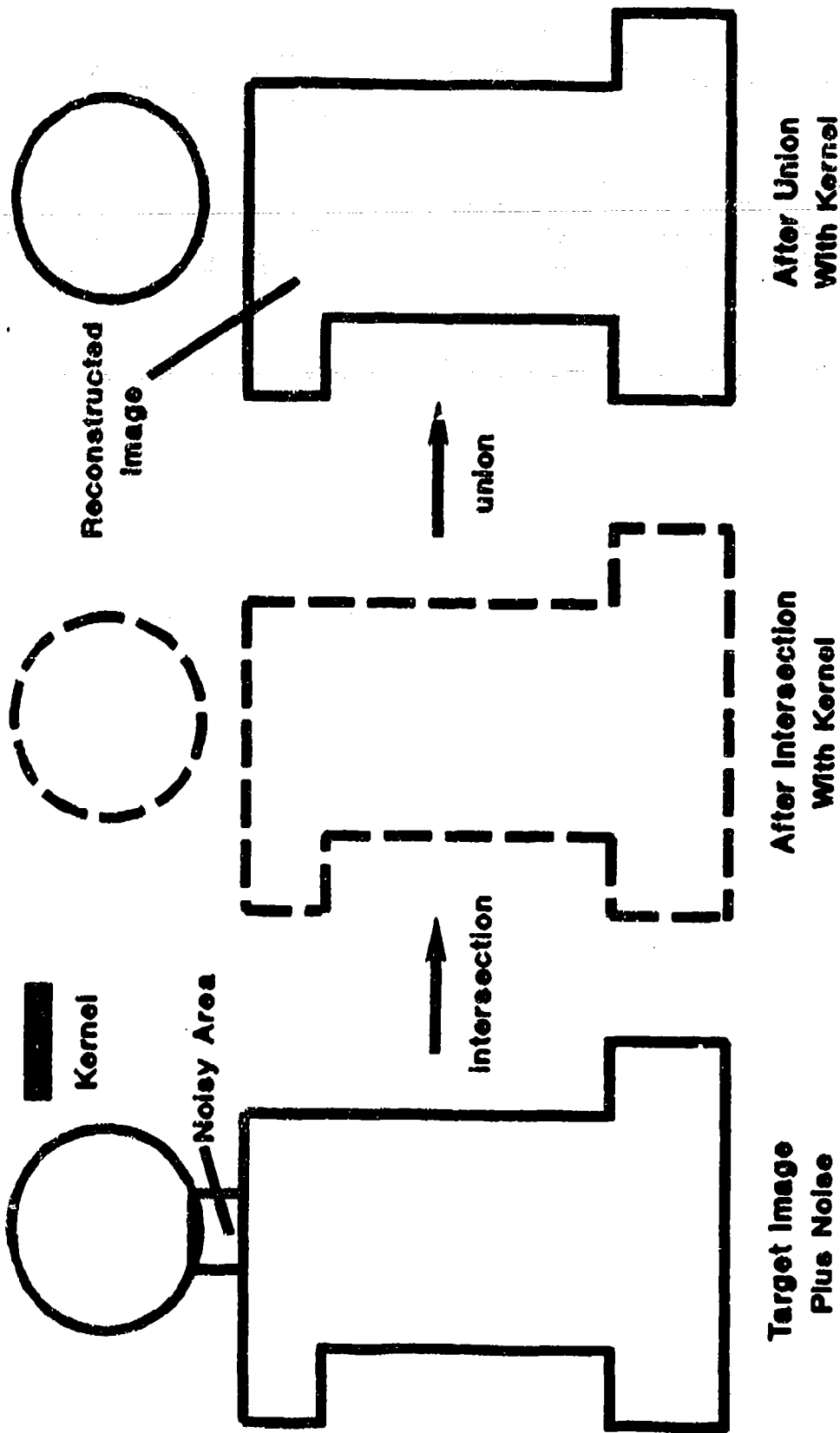


Figure 8
Application of 2-D Morphological Filtering

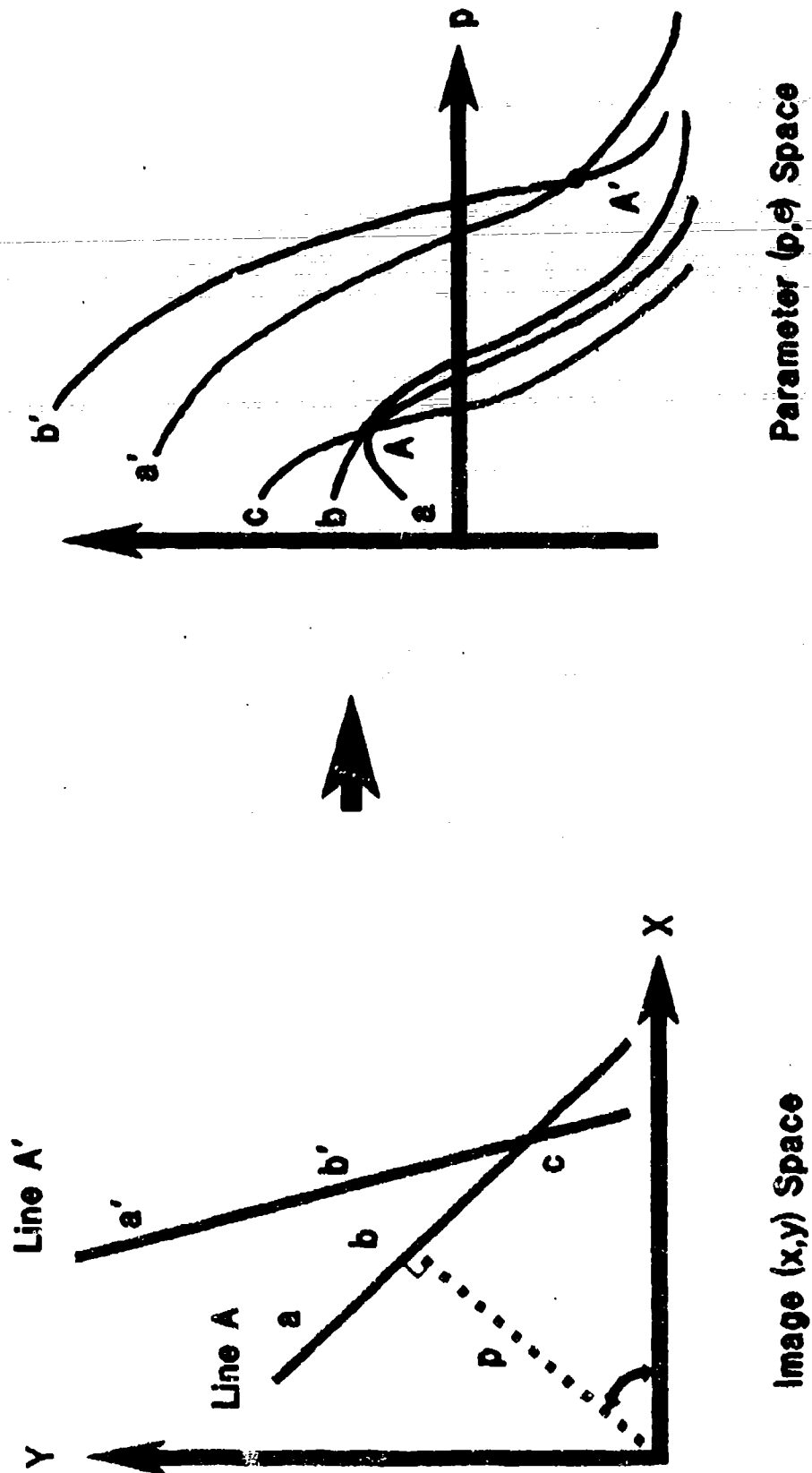


Figure 9
Transformation From Image Space to Parameter Space

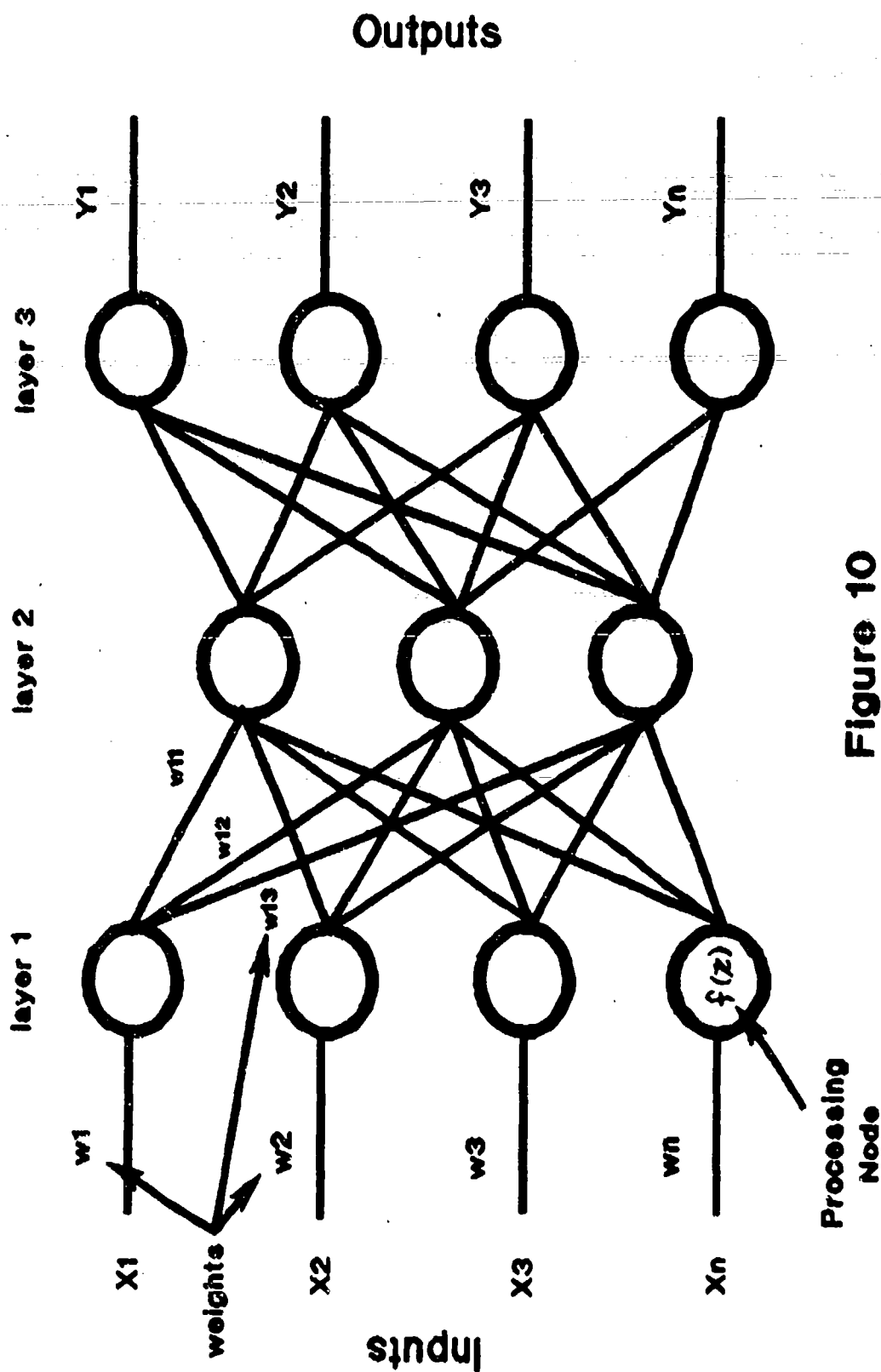


Figure 10
Neural Network Architecture

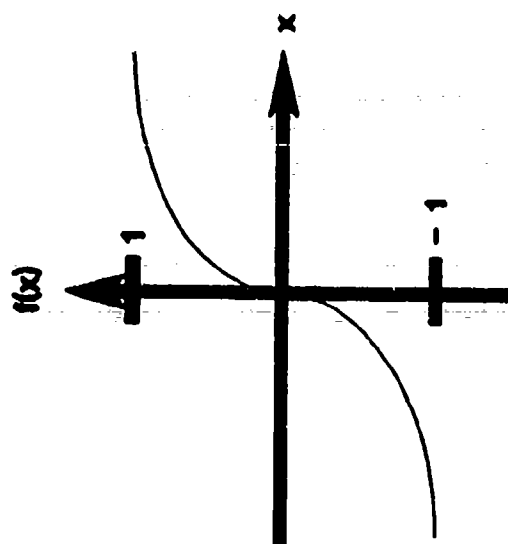


Figure 11
Sigmoid Function

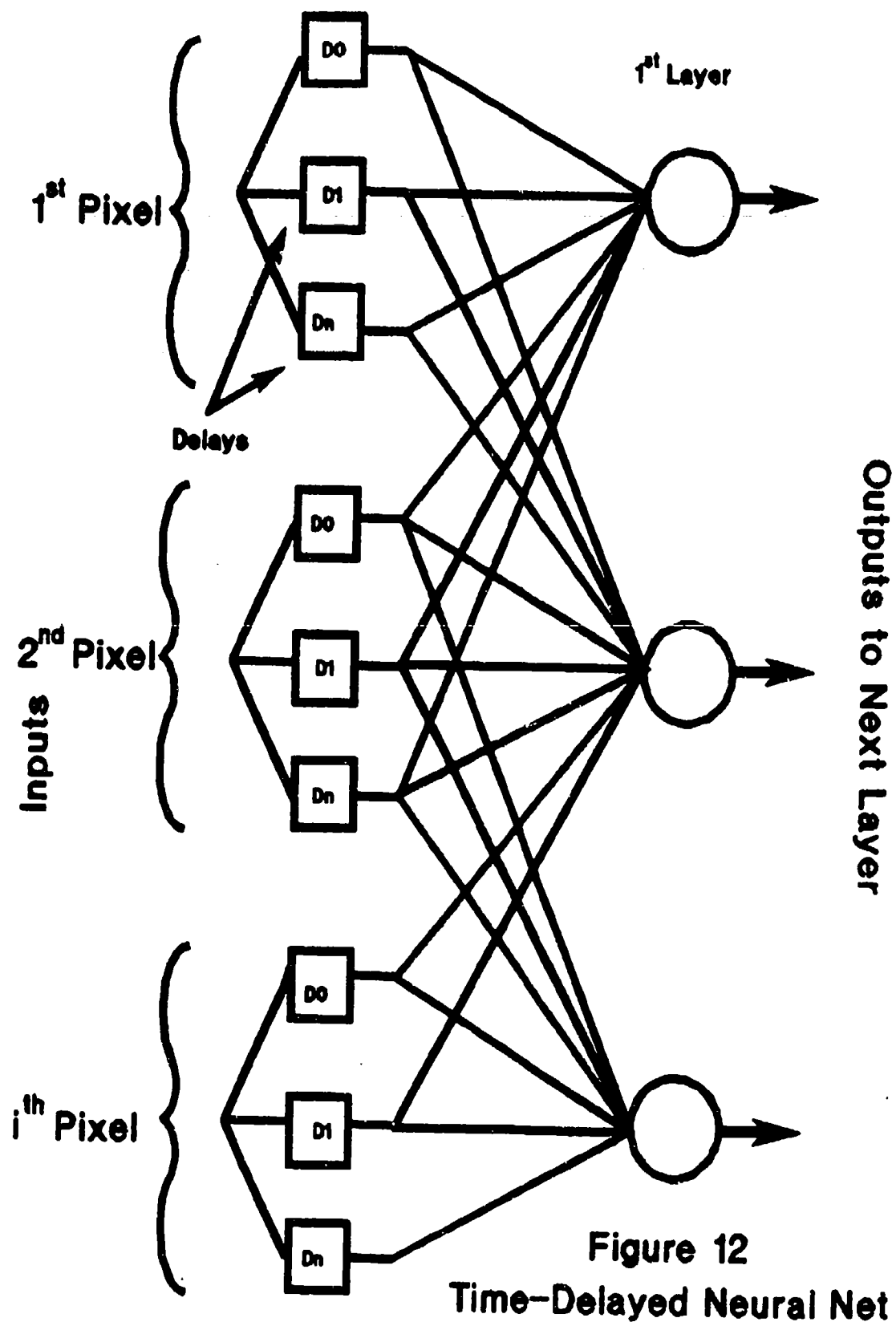


Figure 12
Time-Delayed Neural Net

References

1. H. Vantrees, Detection and Estimation Theory, John Wiley & Sons, New York, New York, 74Vol. I, 1968.
2. M. Skolnik, Introduction to Radar Systems, McGraw-Hill, Second Edition, 1980.
3. Y. Barniv, 'Dynamic Programming Solution for Detecting Dim Moving Targets', IEEE Transactions on Aerospace and Electronics Systems, Vol. AES-21, No. 1, January 1985.
4. B. Jaroszewicz, Application of Dynamic Programming to Track Detection in a Doppler Radar, Final Report to ESD (Contract F19628-89-C-0001), December 1989.
5. J. Arnold, H. Pasternack, 'Detection and Tracking of Low Observable Targets Through Dynamic Programming', The International Society for Optical Engineering, Conference Proceedings (publication pending), April 1990.
6. R. Sittler, 'An Optimal Data Association Problem in Surveillance Theory', IEEE Transactions on Military Electronics, Vol. MIL-8, April 1964.
7. J. Stein, S. Blackman, 'Generalized Correlation of Multi-Target Track Data', IEEE Transactions on Aerospace and Electronic Systems, Vol. AES-11, No. 6, November 1975.
8. A. Corbeil, J. DiDomizio, Track-Before-Detect Development and Demonstration Program, Phase I, Final Report to RADC (Contract F30602-84-C-0036), March 1985.
9. J. Arnold, H. Pasternack, Dynamic Programming Technique for Tracking Dim Targets in Infrared Image Sequences, Final Report to RADC (Contract F30602-89-D-0028), publication

pending (1990).

10 S. Haykin, Communications Systems, 2nd Edition, John Wiley & Sons, New York, 1983.

11. I. Reed, R. Gagliardi, H. Shao, "Application of Three Dimensional Filtering to Moving Target Detection", IEEE Transactions on Aerospace and Electronic Systems, Vol. AES-19, No. 6, November 1983.

12. D. Reid, "An Algorithm for Tracking Multiple Targets", IEEE Transactions on Automatic Control, Vol. AC-24, No. 6, December 1979.

13. Y. Bar-Shalom, T. Fortmann, Tracking and Data Association, Academic Press, Inc., San Diego, CA, 1988.

14. S. Blackman, Multiple-Target Tracking with Radar Applications, Artech House, Inc., Norwood, MA, 1986.

15. R. Stevenson, G. Arce, "Morphological Filters: Statistics and Further Syntactic Properties", IEEE Transactions on Circuits and Systems, Vol. CAS-34, No. 11, November 1987.

16. J. Sklansky, "On the Hough Technique for Curve Detection", IEEE Transactions on Computers, Vol. C-27, No. 10, October 1978.

17. K. Murakami, H. Koshimizo, K. Hasegawa, "On the New Hough Algorithms Without Two-Dimensional Array for Parameter Space to Detect a Set of Straight Lines", IEEE International Conference on Pattern Recognition, 1986.

18. J. Dayhoff, Neural Network Architectures, An Introduction, Van Nostrand Reinhold, New York, NY, 1990

19. R. Lippmann, 'An Introduction to Computing with Neural Nets', IEEE ASSP Magazine, April 1987.

20. A. Waibel, T. Hanazawa, G. Hinton, K. Shikano, K. Lang, 'Phoneme Recognition Using Time-Delay Neural Networks', IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 37, No. 3, March 1989.

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